Equational Model Guided by Real-time Sensor Data to Monitor Industrial Robots

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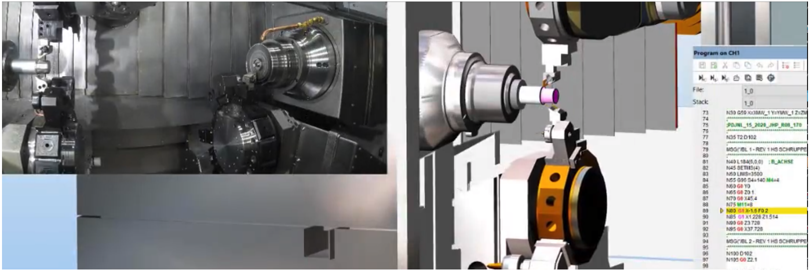
Outline

Motivation



- Industrial robots are used by the experts for manufacturing industrial pieces in the real environment.
- The existed simulators for the milling processes are designed based on **some equational models**.
- Our objective is to **improve the equational model by adding both the environment and the human constraints**, guided by the **sensors data**.

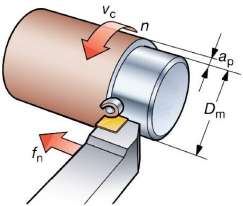
Simulator : NCSimul

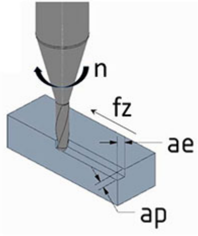
- The NCSimul reads **G-code language** that tells robots where to move, how fast to move, and what path to follow.
- This G-code identifies the tool path, and replicates the material removals by cutting automatically volume.
- NCSimul identifies all syntax errors in the code, crashes in the machining environment, and deviations from the given geometrical form for a to-be-manufactured workpiece.
- The NCSimul assists the machinists to **tune a set of parameters related to the robots, materials, speed and etc** during the manufacturing.

Why NCSimul is not enough ?

NCSimul is not completely faithful to the real manufacturing workshops and the used industrial robots, because it is **not possible to model all the parameters of the machining environment mathematically**.

Simulator : NCSimul





NCSimul uses a set of milling and mechanical formulations for the manufacturing process :

- feed per tooth : $v_f = n \times f_z \times z_c$.
- finishing capability of a cutter : $f_n = \frac{v_f}{n}$.
- volume of removed metal : $Q = \frac{a_e \times a_p \times v_f}{1000}$.
- net power : $P_c = \frac{a_e \times a_p \times v_f}{60 \times 10^6} \times k_c$.
- torque : $M_c = \frac{P_c \times 3 \times 10^3}{\pi \times n}$.

Main Questions to Answer

Main Question

How adapt the formula-based simulators with real-time experiments and complete their missing information into the simulated model.

Some of the missing information is :

- The milling performance regarding various materials and tool types **are not dependent on tool-material changing** with the milling formulas.
- Tools and material conditions are not observable **when the cutting tool is outside the material**.
- We are interested in designing a **simulator that adapts itself** to correct and acceptable **real-time observations**.

To improve the imperfection and difference between the real and simulation conditions during the milling process, we propose **Temporal Probably Approximately Correction (TPAC)** method.

Main Challenge

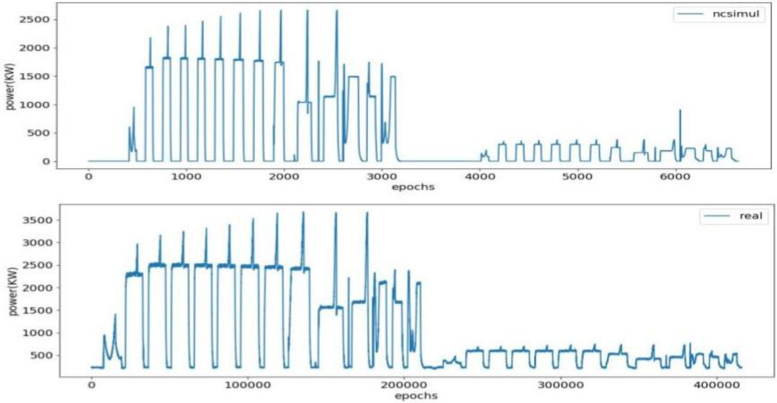


FIGURE – In order to complete the missing information by observing the real milling, we concentrate on power generated signals from simulated and real cases.

Temporal Probably Approximately Correction (TPAC)

- Our approach aligns the **power signals generated by the simulator and the real system**.
- We adjust the simulator by observing the real data and the dynamics of the machines in the context of industrial manufacturing.
- Each triplet (material, tool, workpiece) generates a power signal, we propose an approach that **generalizes this combination for each piecework with different tools, materials and machines**.

$$\forall t \in MT,\ P_{PT}(|R_S^{\beta}(t) - S_{AE}^{\beta}(t)| > \epsilon) < \delta$$

R_S : real dynamic system,
S_{AE} : augmented equational simulator (to-be-learned),
S_E : simulated system,
β : is "Power" in our case.

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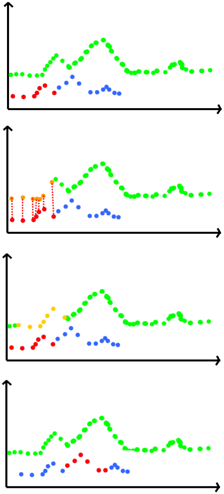
TPAC



$\forall t \in MT,\ P_{PT}(|R_S^{\beta}(t) - S_{AE}^{\beta}(t)| > \epsilon) < \delta$

R_S : real dynamic system,
S_{AE} : augmented equational simulator (to-be-learned),
β : is "Power" in our case.

Parameters to fix in the algorithm :
$W, W_0, step = \alpha W, \epsilon, \delta$

Building Augmented Simulator for Power Signals

In this algorithm the existing electric power by simulator $S_E^{\texttt{power}}$ is guided by real data D to follow the real signal $R_S^{\texttt{power}}$.

For a given current step started at time t_c and a given window W, find

$$f : \{t_c - W, \cdots, t_c + W\} \longrightarrow \{t_c - W, \cdots t_c + W\}$$

such that $\forall\ t_c - W \leq t \leq t_c + W$, $S_E(f(t))$ aligns $R_S(t)$.

$$\min_{f, W_0} \sum_{[t_i, t_i+W_0] \subset [t_c - W, t_c + W]} |a(t_i, W_0) - 1.0| + |b(t_i, W_0)|$$

$$a(t_i, W_0) = \frac{cov(A, B)}{var([S_E(f(t_i)), S_E(f(t_i + W_0))])}$$

$$b(t_i, W_0) = mean([R_S(t_i), R_S(t_i + W_0)]) - a(t_i, W_0) mean([S_E(f(t_i)), S_E(f(t_i + W_0))])$$

Where $B = [S_E(f(t_i)), S_E(f(t_i + W_0))]$ and $A = [R_S(t_i), R_S(t_i + W_0)]$.

Data Description

- The simulated and real data are available for various material-cutting tool-workpiece combinations.
- The simulated data is generated by the NCSimul software, and the real one is generated by the real observed data in a real factory (UF1 company).
- We extract around 1.7 GB data in total.
- We use data for manufacturing :
  - two workpieces : GP2R and 5axes,
  - two types of cutting tools : long (2 different cutting tools) and short (2 different cutting tools),
  - and two materials : steel and aluminium.
- Because of some limitations for applying the sensors in the real workshop, the only registered data for the real observations is the consumed electrical power (P_c).

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Selected Parameters for the Algorithm

Values of parameters for the TPAC algorithm :

- Steel material : $W = 15000$, $W_0 = 500$, step $= 50$ and $\epsilon = 0.0$
- Aluminium material : $W = 45000$, $W_0 = 500$, step $= 50$ and $\epsilon = 0.6$

Experimental Results

Our results show how the missing information can be completed by our augmented simulation [1 2].

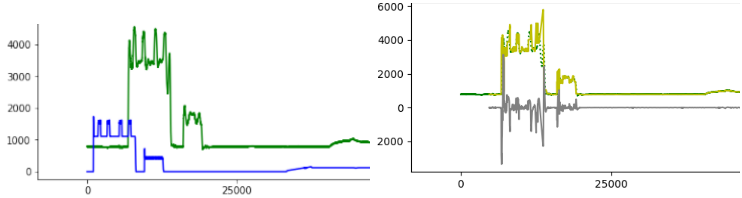

FIGURE – Part of the power signals for the pocket end milling of the **GPR2** with **steel** material and a **short tool**.

Vertical axe : power, horizontal axe : time steps.

R_S : green, S_E : blue, S_{AE} : golden.

Experimental Results

Our method does not only correct the simulator w.r.t. the real observed data, it also detects the anomalies during the real manufacturing performance. [3 4].

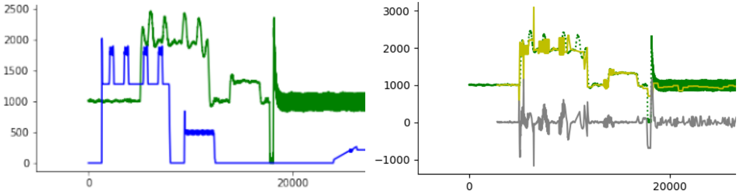

FIGURE – Part of the power signals for the pocket end milling of the **GPR2** with **aluminium** material and a **short tool**.

Vertical axe : power, horizontal axe : time steps.

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Eperimental Reults

our approach is noise resistant specially for the soft materials as aluminium. Our augmented simulator corrects the machinist's generated [5, 6].

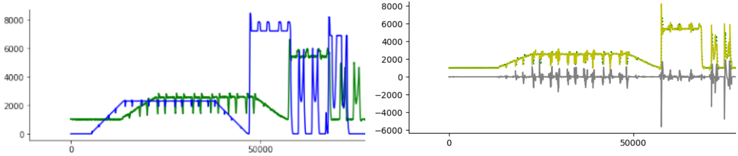

FIGURE – Part of the power signals for the pocket milling of the **GPR2** with **aluminium** material and a **short tool**.

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Conclusion and Future Works

- We propose and formalize an approach that **integrates real and environmental constraints through sensor data analysis into equational models of simulators**.
- This approach **performs a continuous adjustment of the simulator w.r.t. the real system** to ensure a continuous monitoring of industrial robots.
- The experiments show that our proposed augmented simulator :
  - It takes into account **material stiffness** by adding real data and more generally.
  - It is **adaptable to the used materials** (e.g. steel or aluminium), cutting tool workpiece and tools.
  - It can also correct the simulation results when **the cutting-robot is outside the material** or when **the industrial process is stopped temporally** for any external reason.
  - It is **robust toward the noisy real conditions** and **can solve difficult cases** where the real and simulated values have a **complex and non-linear differences**.